Institutions and the Value of Nonpoint Source Measurement Technology: Carbon Sequestration in Agricultural Soils

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Abstract

The development of technologies for accurate field-scale carbon assessment allows the implementation of more efficient policies than can be implemented in their absence. We estimate the value of accurate measurement technology by estimating the gains from implementing a more efficient policy, one that targets carbon reductions at the field scale but requires accurate field-scale measurement technology, relative to a practice-based policy that can be implemented in the absence of such technology. We find large cost savings due to improved targeting of conservation tillage subsidies for the state of Iowa. The cost savings depend significantly on the choice of baseline carbon, while the ability of the government to cost discriminate has little impact on the value of accurate measurement technology.

Keywords: carbon sequestration, green payment policy, value of measurement technology.

INSTITUTIONS AND THE VALUE OF NONPOINT SOURCE MEASUREMENT TECHNOLOGY: CARBON SEQUESTRATION IN AGRICULTURAL SOILS

Introduction

Agricultural nonpoint source pollution continues to be a major source of environmental degradation in many areas of the United States. As argued in Millock, Sunding, and Zilberman (2002), the major challenge for regulating nonpoint source effluents is the lack of accurate information and effective measurement of the emission contributions of individual polluters. However, the line between point and nonpoint sources is becoming increasingly blurred: with improved measurement technologies, traditional nonpoint sources can become point sources. For example, large farming operations in California are effectively point sources and the development of GIS technology for tracking effluents will "turn" more such nonpoint sources into point sources. Thus, the further development of such measurement technologies can significantly improve social welfare if these technologies can turn additional nonpoint to point sources.

Unfortunately, there has not been much systematic empirical evaluation of measurement technologies in the literature. The objective of this paper is to provide such an evaluation for technologies that can measure field-level carbon sequestration in the context of either a government program of terrestrial carbon sequestration or a carbon market. Such technologies already exist, but significant work remains,[1] and Mooney et al. (2002, 2003) provide estimates of the current costs of certain of these sampling technologies.

Here, we empirically estimate the value of accurate measurement technology by comparing the sequestered carbon levels in a practice-based subsidy policy implemented with and without measurement of carbon storage on individual fields. We consider four possible levels of measurement technology that vary in their accuracy: those that provide accurate measurements of soil carbon content at the field level (the most accurate), the county level (i.e., providing accurate county averages), the crop reporting district level, and finally the statewide level. Focusing on a practice-based government sponsored subsidy policy, we also consider several categories of institutional constraints, including the choice of baseline carbon and the ability of the government to discriminate cost. Under each institutional setting, we identify the optimal policy design or subsidy schemes given the technology level. We then calculate the carbon gains and the associated monetized values as the technology improves.

There has been considerable excitement in the agricultural community over the prospect of utilization of agricultural soils to sequester carbon as well as to grow crops so that farmers could benefit economically from adopting practices that generate carbon storage. In a much-quoted study, Lal et al. (1998) estimate that agricultural soils in the United States have the potential to sequester between 75 and 208 mmt of carbon per year. While the exact manner in which agricultural enterprises might financially profit from adopting practices that sequester carbon are not yet developed, possibilities include the emergence of formal carbon markets and the direct payment of subsidies to farmers through a government program (Feng, Zhao, and Kling 2003).

In this paper, we concentrate on a potential government program similar to the recently adopted Conservation Security Program (CSP) in the 2002 farm bill where subsidies are paid to farmers who adopt environmentally friendly practices (U.S. Congress 2002). In particular, payments could be directed toward agricultural practices believed to sequester carbon, such as conservation tillage. Given heterogeneity in land and farmer characteristics, soil quality, and weather, fields with higher sequestered carbon per dollar of subsidy should be targeted. However, if field-level carbon sequestration information is not available, the program has to target larger regions for which sequestered carbon can be measured. Targeting has been shown to produce significant efficiency gains in a number of cases (Parks and Hardie 1995, Pautsch et al. 2001, Antle, Capalbo, and Mooney 2002, Antle et al. 2003).

We further focus on two aspects of program design that affect the gains from field-level measurement. One is the choice of baseline: whether payment is made only for carbon stored above an initial baseline (perhaps the level of carbon contained in the soil in the year the program begins) or whether payment is based on the total amount of carbon stored in the soil. In the first case, previous adopters of practices that promote carbon storage would not be eligible for the subsidy. Limited conservation budgets favor paying for new carbon only, but such a program would seem to penalize farmers who have adopted conservation tillage in the past. We consider both policy options in our evaluation of measurement technologies and explicitly measure the difference in the implied value of the measurement technology under these two institutional regimes.

A second critical program design element is the extent to which the government can differentiate its payments to farmers when field-level carbon sequestration potentials are not known. If regulators know the average carbon sequestration level in a region (such as a county, watershed, or state), they may find it impractical to pay different prices for adopting carbon sequestration practices within those regions, even though in actuality farmers may have different reservation prices. While the most cost-effective program would target farmers who are willing to adopt at the lowest cost, such price discrimination may not be possible for several reasons. There may be information asymmetries wherein the government cannot determine which farmers would be willing to supply carbon sequestration at lower costs than others when field-scale measurement technology is not available. Alternatively, the government may not wish to price (or cost) discriminate even if an efficient bid system could be designed to reveal farmers' costs, as the government may want to provide rents to low-cost suppliers as a form of income transfer. Finally, political pressures may prevent this kind of cost discrimination.

Thus, in assessing the value of more accurate measurement technologies for carbon sequestration in agricultural soils, we consider four institutions, each representing a different combination of the design features just enumerated. They are (1) paying for all carbon measured in the soil versus paying only for carbon above an initial baseline, and (2) cost discrimination where farmers with lower opportunity costs receive lower payments versus equal payment amounts for all farmers in a geographically designated subset. Note that when accurate field-scale measurement technology is available, the ability to cost discriminate is complete, as full information on the carbon levels at the farm field is available to both farmers and regulators.

Subsidy Policies under Alternative Measurement Technologies and Institutions

Suppose there are I farms, indexed by $i = 1,...,I$. For farmer *i*, let A_i be the acreage of homogeneous land and let q_i be the amount of carbon that can be sequestered per acre of land in conservation tillage. Let $p_i(s)$ be the farmer's probability of adopting conservation tillage given a per acre subsidy of *s*, which is observed by the government.[2] We assume that $p'_i \geq 0$ and $p''_i \leq 0$ for all *i:* a higher subsidy raises the adoption probability but at a decreasing rate. Note that for some farmers, it is possible that $p_i(0) = 1$, implying that even without any subsidy they find it profitable to adopt conservation tillage.

Subsidy Policies with Accurate Field-Scale Measurement Technology

If the regulator is able to measure the carbon levels sequestered in a field, it will be possible to target payments to fields that can most cost-effectively sequester carbon. Consider first the case of a subsidy payment for new carbon only: the regulator observes q_i and offers different subsidies to different farms for new lands in the sequestration program based on q_i and $p_i(s)$. Given a budget of B, the government chooses the payment profile $\mathbf{s} = (s_1, ..., s_I)$ to maximize the expected amount of sequestered carbon:

$$\begin{aligned} &\max_{\mathbf{s}} \sum_{i=1}^{I} p_i(s_i) A_i q_i \\ \text{s.t.} \quad &\sum_{i=1}^{I} \left(p_i(s_i) - p_i(0) \right) A_i s_i = \mathrm{B}; \quad \mathrm{s}_i \geq 0 \end{aligned} \tag{1}$$

where $\left(p_i(s_i) - p(0) \right) A_i$ measures the expected new acreage in the sequestration program.[3] Let λ_1^I be the Lagrange multiplier, which measures the additional expected carbon sequestered when budget B increases by one unit. The subscript denotes the institution and the superscript "I" denotes that the regulator has accurate information about the field-scale carbon levels. Then the Kuhn-Tucker conditions for the optimal s_i are

$$\begin{aligned} &q_i p_i^{'}(s_i) - \lambda_1^1 s_i p_i^{'}(s_i) - \lambda_1^1 \left(p_i(s_i) - p_i(0) \right) \leq 0 \\ &s_i \geq 0 \\ &[(q_i p_i^{'}(s_i) - \lambda_1^1 s_i p_i^{'}(s_i) - \lambda_1^1 \left(p_i(s_i) - p_i(0) \right)] s_i = 0. \end{aligned} \tag{2}$$

Let $\mathbf{s}_1^I = (s_{1i}^I, i = 1, ..., I)$ be the optimal solutions. For all farmers with $s_{1i}^I > 0$, (2) implies

$$\frac{q_i}{s_{1i}^I + \dfrac{p_i(s_{1i}^I) - p_i(0)}{p_i'(s_{1i}^I)}} = \lambda_1^I \,. \tag{3}$$

Assumption $p_i'' \leq 0$ implies that $(p_i(s_i) - p_i(0)) / p_i'$ increases in s_i (or p_i): a farmer who is more willing to adopt (i.e., who has a higher probability of adoption) should receive a lower level of subsidy. Of course, s_{1i}^I increases in q_i: farmers with higher sequestration potential should receive higher subsidies.

We now turn to the case where the policy includes payment for all carbon, regardless of whether it was sequestered prior to the initiation of the subsidy program or not.[4] The problem becomes

$$\begin{aligned} &\max_{\mathbf{s}} \sum_{i=1}^{I} p_i(s_i) A_i q_i \\ \text{s.t.} \quad &\sum_{i=1}^{I} p_i(s_i) A_i s_i = \text{B}; \quad \text{s}_i \geq 0 \end{aligned} \tag{4}$$

Let λ_2^I be the associated Lagrange multiplier, and $\mathbf{s}_2^I = (s_{2i}^I, i = 1, \ldots, I)$ the optimal solutions. The optimality conditions are similar to (2), and for all farmers with $s_{2i}^I > 0$, we know

$$\frac{q_i}{s_{2i}^I + \dfrac{p_i(s_{2i}^I)}{p_i'(s_{2i}^I)}} = \lambda_2^I \,. \tag{5}$$

Again, s_{2i}^I decreases in p_i: farmers with higher adoption probabilities receive lower payments.

It is clear that more carbon is sequestered under (1) than under (4): essentially the budget level is higher by $\sum_{i=1}^{I} p_i(0) A_i s_i$ if only new carbon sequestered is eligible for payment.

Subsidy Policies in the Absence of Accurate Field-Scale Measurement Technology

If field-scale measurement technology of sufficient accuracy is not available to regulators, the precise targeting schemes discussed in the previous section cannot be implemented. In this case, the regulator might divide the country or region into zones that are somewhat agronomically and/or ecologically similar and use the average carbon sequestration potential to implement policies. Possible subsets include county, crop reporting district, or state. Let $\mathcal{I} = \{1, ..., I\}$ be the entire set of farms, and $\mathcal{I}_k, k = 1, ..., K$ be a partition of $\mathcal{I}$, that is, $\bigcup_{k=1}^{K} \mathcal{I}_k = \mathcal{I}$. For each subset $\mathcal{I}_k$, we assume that policymakers can obtain accurate information about the average per acre sequestration potential q^k, where

$$q^k = \frac{\sum_{i \in \mathcal{I}_k} A_i q_i}{\sum_{i \in \mathcal{I}_k} A_i}. \tag{6}$$

Thus, while regulators recognize the differences in carbon sequestration across the subset, they must treat farms within each subset as homogeneous: $q_i = q^k$ for $i \in \mathcal{I}_k$.[5] The extreme case of field-level information corresponds to $\mathcal{I}_k$ being singletons (with $K = I$), and that of no information corresponds to $K = 1$.

Given information represented by the partition $\mathcal{I}_k, k = 1, ..., K$, we consider four policy institutions under which the regulator might choose the subsidy levels, listed in Table 1. Under institution 1, the subsidy is for new carbon only, and even for farmers in the same subset $\mathcal{I}_k$, the regulator can still differentiate subsidies based on the cost of adoption represented by the adoption probabilities. This might reasonably occur if a bidding system similar to the one used in the CRP program is used to generate bids from which the regulator can select farms for the program. Institution 2 is similar except that

TABLE 1. The policy institutions of carbon sequestration

	Cost Discrimination	**No Cost Discrimination**
Payment for new carbon	Institution 1	Institution 3
Payment for all carbon	Institution 2	Institution 4

all land in conservation tillage receives the subsidy, regardless of when conservation tillage was adopted. In both cases, farmers within the same subset can receive different subsidies: $s_i \neq s_j$ for $i, j \in \mathcal{I}_k$, if $p_i(s) \neq p_j(s)$. Thus, the limited information means that the government cannot identify and select farms that are particularly high in carbon sequestration for inclusion in the program, but it can select lower-cost providers.

Under institutions 3 and 4, however, we assume that cost discrimination is not possible within a subset, because of the limited information the regulator has about sequestration potential. In either case, those within the same subset receive the same subsidy: $s_i = s_j$ for $i, j \in \mathcal{I}_k$, even if $p_i(s) \neq p_j(s)$, although the subsidies can vary across subsets.

Under the institution 1, given partition $\mathcal{I}_k, k = 1,...,K$, the government's optimization problem is similar to equation (1), except that q_i is replaced by q^k for $i \in \mathcal{I}_k$:

$$\begin{aligned} &\max_{\mathbf{s}} \sum_{\mathrm{k=1}}^{\mathrm{K}} \left[\sum_{i_k \in \mathcal{I}_k} p_{i_k}(s_{i_k}) A_{i_k} \right] q^k \\ \text{s.t.} \quad &\sum_{\mathrm{k=1}}^{\mathrm{K}} \left[\sum_{i_k \in \mathcal{I}_k} \left(p_{i_k}(s_{i_k}) - p_{i_k}(0) \right) A_{i_k} s_{i_k} \right] = \mathrm{B}; \quad \mathrm{s}_i \geq 0,\ i \in \mathcal{I} \end{aligned} \tag{7}$$

Let λ_1^K be the associated Lagrange multiplier, where subscript 1 denotes institution 1, and superscript *K* represents partition with *K* subsets (*K*, unlike *k*, is not an index). Note that typically $\lambda_1^K \neq \lambda_1^I$ for $K < I$. Let $\mathbf{s}_1^K = (s_{1i_k}^K, i_k \in \mathcal{I}_k, k = 1,...,K)$ be the optimal solutions. Corresponding to (3), we know that for all $s_{1i_k}^K > 0$,

$$\frac{q^k}{s_{1i_k}^K + \dfrac{p_{i_k}(s_{1i_k}^K) - p_{i_k}(0)}{p'_{i_k}(s_{1i_k}^K)}} = \lambda_1^K, \quad i_k \in \mathcal{I}_k, \quad k = 1,...,K. \tag{8}$$

Thus, farmers in subsets with higher average sequestration potentials tend to receive higher subsidies, and those who are more willing to adopt conservation tillage (i.e., those with higher p_{i_k}) tend to receive lower subsidies.

Under institution 3, the government can choose only a single subsidy for farmers within the same subset, although subsidies can vary across subsets. The decision problem is

$$\begin{aligned} &\max_{s^1,\ldots,s^K} \sum_{k=1}^{K}\left[\sum_{i_k\in\mathcal{I}_k} p_{i_k}(s^k)A_{i_k}\right]q^k \\ \text{s.t.} \quad &\sum_{k=1}^{K}\left[\sum_{i_k\in\mathcal{I}_k}\left(p_{i_k}(s^k)-p_{i_k}(0)\right)A_{i_k}\right]s^k = \mathrm{B}; \quad \mathrm{s}^k \ge 0,\ i=1,\ldots,K. \end{aligned} \tag{9}$$

Let λ_3^K be the associated Lagrange multiplier, where subscript 3 denotes institution 3, and superscript *K* represents partition with *K* subsets. Let

$$p^k(s)=\frac{\sum_{i_k\in\mathcal{I}_k} A_{i_k}p_{i_k}(s^k)}{\sum_{i_k\in\mathcal{I}_k} A_{i_k}} \tag{10}$$

be the weighted average probability of adoption of subset *k*, and $p^{k\,'}(s)=dp^k(s)/ds$. Let $\mathbf{s}_3^K=(s_{3i}=s^k,\ i\in\mathcal{I}_k, k=1,\ldots,K)$ be the optimal solutions. Then, similar to (8), for all subsets receiving positive subsidies, $s^k>0$, we have

$$\frac{q^k}{s^k+\dfrac{\sum_{i_k\in\mathrm{I}_k} A_{i_k}\left(p_{i_k}(s^k)-p_{i_k}(0)\right)}{\sum_{i_k\in\mathrm{I}_k} A_{i_k}p\,'_{i_k}(s^k)}}=\frac{q^k}{s^k+\dfrac{p^k(s^k)-p^k(0)}{p^{k\,'}(s^k)}}=\lambda_3^K,\quad k=1,\ldots,K. \tag{11}$$

Thus, subsets with a higher average level of carbon potential q^k receive higher subsidies. Further, $p_i^{''}\le 0$ implies that $p^k/p^{k\,'}$ increases in s^k: subsets with lower costs of adoption or higher $p^k(s)$ will receive a lower subsidy. Notice that since the subsidy can vary across subsets, the government factors in the probability differences across subsets in its optimal decision.

The optimality conditions for institutions 2 and 4 can be developed similarly. The optimal subsidies are denoted as $\mathbf{s}_2^K=(s_{2i_k}^K, i_k\in\mathcal{I}_k, k=1,\ldots,K)$ and $\mathbf{s}_4^K=(s_{4i}=s^k,\ i\in\mathcal{I}_k, k=1,\ldots,K)$ respectively. Recall that with the field-level information, institution 1 (institution 2) is the same as institution 3 (institution 4). Thus,

$$\mathbf{s}_1^I = \mathbf{s}_3^I, \quad \mathbf{s}_2^I = \mathbf{s}_4^I. \tag{12}$$

The Value of Improved Measurement Technologies

Regardless of the information and institutions, for a given budget level, in order to compare the efficiency of the various subsidy choices, we need only compare how much expected carbon can be sequestered. Let $Q(\mathbf{s})$ be the expected total sequestered carbon given payment profile **s**:

$$Q(\mathbf{s}) = \sum_{i \in \mathcal{I}} p_i(s_i) A_i q_i . \tag{13}$$

Then, given a measurement technology represented by partition $\{\mathcal{I}_k, k = 1,..., K\}$, the expected total carbon levels under institution l is $Q(\mathbf{s}_l^K)$, $l = 1,...,4$. The case of field-level information under institution 1, $\mathbf{s}_1^I$, sequesters the maximum level of carbon, since by definition, $\mathbf{s}_1^I$ maximizes $Q(\mathbf{s})$ given budget B. Under other institutional and information settings, the optimal payments are limited by information about q_i, cost discrimination, or paying for all carbon.

For a given institution, the expected carbon $Q(\mathbf{s})$ increases as the measurement technology improves, that is, as the partition $\{\mathcal{I}_k, k = 1,..., K\}$ becomes "finer" (see Appendix A for the proof). Under institution *l*, the gain from information $\{\mathcal{I}_k, k = 1,..., K\}$ to field-level measurement is $Q(\mathbf{s}_l^I) - Q(\mathbf{s}_l^K)$, which can be expressed in monetary terms as

$$G(\mathbf{s}_l^I; \mathbf{s}_l^K) = \frac{Q(\mathbf{s}_l^I) - Q(\mathbf{s}_l^K)}{\lambda_1^I} \tag{14}$$

where λ_1^I is the Lagrange multiplier obtained in equation (1). Obviously, $G(\bullet)$ decreases as $\{\mathcal{I}_k, k = 1,..., K\}$ becomes finer.

Throughout the comparisons, we use $1/\lambda_1^I$ to measure the marginal value of carbon for consistency across comparisons. This value changes as budget B varies. If there is an efficient carbon-trading program, we could also use the market price of carbon. Note that the market price should equal $1/\lambda_1^I$ if the sequestration program is designed efficiently.

For a given measurement technology, we know that more carbon can be sequestered under institution 1 (institution 2) than under institution 3 (institution 4), because under the former, even within the same subset, the government can still "cost discriminate," or choose payment levels based on each farmer's adoption probability. That is, $Q(\mathbf{s}_1^K) > Q(\mathbf{s}_3^K)$ and $Q(\mathbf{s}_2^K) > Q(\mathbf{s}_4^K)$ for $K < I$. Consequently, from equations (14) and (12), we know $G(\mathbf{s}_1^I;\mathbf{s}_1^K) < G(\mathbf{s}_3^I;\mathbf{s}_3^K)$ and $G(\mathbf{s}_2^I;\mathbf{s}_2^K) < G(\mathbf{s}_4^I;\mathbf{s}_4^K)$: if we start with the same information structure, field-level measurement technologies are more valuable under institution 3 (institution 4) than under institution 1 (institution 2).

Although for any given technology, the expected carbon sequestration level is higher under institution 1 (institution 3) than under institution 2 (institution 4), no clear-cut comparison can be made in terms of the value of improved technology under paying for all versus paying for new carbon. In fact, as we will show later, the ranking can be reversed as the budget level changes.

The Interpretation of Baselines

In the previous discussion, the regulator has been assumed to be concerned with the total amount of carbon sequestered after the choice of subsidies. However, in some contexts it will be the amount of newly sequestered carbon as a result of a particular policy that will be of interest to regulators.[6] Notice that the same optimal payment profile $\mathbf{s}_1^I$ and marginal value of carbon $1/\lambda_1^I$ as found in equation (1) can be obtained in the following setup where only new carbon sequestered is considered:

$$\begin{aligned} &\max_{\mathbf{s}} \ \sum_{i=1}^{I} p_i(s_i)A_i q_i - \sum_{i=1}^{I} p_i(0)A_i q_i \\ \text{s.t.} \quad &\sum_{i=1}^{I}\left(p_i(s_i) - p_i(0)\right)A_i s_i = \text{B}; \quad s_i \geq 0. \end{aligned} \tag{15}$$

Here, the objective function measures the net increase in the expected total carbon from using $\mathbf{s}$ relative to no payment, or the new carbon. The term $\sum_{i=1}^{I} p_i(0)A_i q_i$ measures the baseline level of carbon sequestration without any payment. Similarly, under other informational and institutional settings, we can subtract the baseline carbon in the objective function and obtain the same optimal payment profiles. Thus, the choice of the baseline carbon level in the objective function simply reflects an accounting issue and does not affect the optimal payment profile, the marginal value of additional sequestered carbon, or the value of improved measurement technologies. In contrast, whether the government pays only for the new carbon or for all carbon does affect these values. When existing adopters of conservation tillage receive payments under a carbon program, less of the budget will remain for the purchase of new carbon and therefore less total (and new) carbon will be sequestered.

Empirical Models and Data

In this section, we describe the empirical analysis that we rely on to obtain the adoption probabilities $p_i(s)$ and the carbon potential q_i, which we use in the next section to simulate the consequences of the various subsidy policies and to compute the value of improved measurement technology. We obtain the adoption probabilities from an economic model of conservation tillage adoption, while we used carbon potentials obtained from a physical process model. The set of farms $\mathcal{I}$ contains some 13,345 National Resource Inventory (NRI) (USDA-SCS 1994) points for the state of Iowa.

To obtain the adoption probabilities, we draw on the work of Kurkalova, Kling, and Zhao (2003), which presents empirical estimates of a reduced-form, discrete-choice adoption model for conservation tillage in Iowa. The Kurkalova, Kling, and Zhao model assumes that a farmer will adopt conservation tillage if the expected annual net return to using conservation tillage (π_1) exceeds the expected net return from using conventional tillage (π_0) plus the premiums associated with uncertainty $P(\sigma_1^2, \sigma_2^2, \mathbf{z})$, which in turn depends on the variability of the net returns to conservation tillage, σ_1^2, conventional tillage, σ_0^2, and other explanatory variables ($\mathbf{z}$). With the addition of a standard econometric stochastic component with variance, σ, the probability that a farmer will adopt conservation tillage can be written as[7]

$$\Pr\left[adopt\right] = \Pr\left[\pi_1(\mathbf{x}) \geq \overline{\pi}_0 + P(\sigma_1^2, \sigma_2^2, \mathbf{z}) + \sigma\varepsilon\right].$$

For the purposes of our study, we utilize the ability of this model to predict the probability of adoption in response to a subsidy. In particular, the adoption probability of farmer i is

$$p_i(s_i) = \frac{\exp\left(\frac{1}{\sigma}\left\{s_i + \pi_{1,i} - \pi_{0,i} - P_i\right\}\right)}{1 + \exp\left(\frac{1}{\sigma}\left\{s_i + \pi_{1,i} - \pi_{0,i} - P_i\right\}\right)}. \tag{16}$$

The field-specific potential of soil to sequester carbon, q_i, was estimated at each of the data points using the Environmental Policy Integrated Climate (EPIC) model, version 1015 (Izaurralde et al. 2002)[8]. The simulations were carried out at a field-scale level for areas homogeneous in weather, soil, landscape, crop rotation, and management system parameters. Version 1015 of EPIC includes an updated (relative to earlier versions) carbon simulation routine that is based on the approach used in the Century model developed by Parton et al. (1994).

At each of the data points, two 30-year simulations were run, one under conventional tillage and the other assuming conservation tillage. The NRI database provided the land use and other input data for the simulations. We computed the quantity q_i as the difference between soil carbon content under conservation tillage and that under conventional tillage, averaged over the 30 years. Figure 1 shows a plot of carbon sequestration potential data for Iowa, where counties with different carbon sequestration potentials are highlighted by a color scheme. For the state as a whole, the average q is 0.203 ton/acre/year (with the associated standard deviation being 0.095).

As previously noted, the basic data come from the NRI (Nusser and Goebel 1997). For the purposes of our estimation, we treat each NRI point as representing a producer with a farm size A_i equal to the number of acres represented by the NRI expansion factor.

Results

For each of the subsidy schemes and institutions described earlier, the regulator's problem of maximizing the total new expected carbon sequestration subject to the budget constraint was solved numerically using the data for I=13,345 Iowa NRI points.

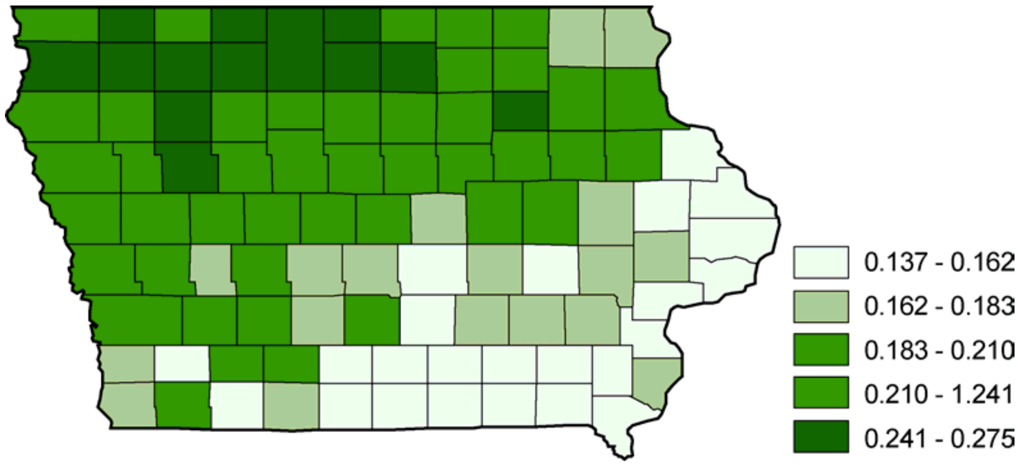

FIGURE 1. Per county average carbon sequestration potential, tons per acre per year

We considered 20 levels of potential budgets, based on the budget amount from the federal funding that might be available to Iowa through the CSP.[9] At each of the budget levels, we computed the expected quantity of carbon sequestration $Q(\mathbf{s}_l^K)$ under institution l and partition with K subsets. Here $K = I$, 99, 9, 1 correspond to four levels of measurement available: field level ($K = I$), county level ($K = 99$), crop reporting district level ($K = 9$), or state level ($K = 1$). The details of computations are provided in Appendix B.

Figure 2 compares the marginal costs of carbon sequestration under institutions 1 and 2 given field-scale measurement, $1/\lambda_1^I$ and $1/\lambda_2^I$. As expected, the marginal costs are lower when only new adopters are being paid. We estimate that some 500,000 mt of carbon can be sequestered annually at the marginal cost of \$30 per mt if new adopters are being paid only, and at the marginal cost of almost \$100 per mt if all adopters are being paid.

Figure 3 depicts the amount of new carbon obtainable annually, $Q(\mathbf{s}_l^{99})$, under the four institutions ($l = 1, 2, 3, 4$), assuming that only county-level information is available. As with the marginal costs, who is being paid makes a crucial difference in the amount of sequestered carbon. The ability of a policy to cost discriminate has a relatively small impact on the amount sequestered when who is being paid is held constant, as $Q(\mathbf{s}_2^{99})$ is very similar to $Q(\mathbf{s}_4^{99})$, and $Q(\mathbf{s}_1^{99})$ is virtually indistinguishable from $Q(\mathbf{s}_3^{99})$ in Figure 2.

To assess the value of field-level monitoring technology, Figure 4 presents the carbon benefits associated with moving from county-level targeting ($K = 99$) to field-scale

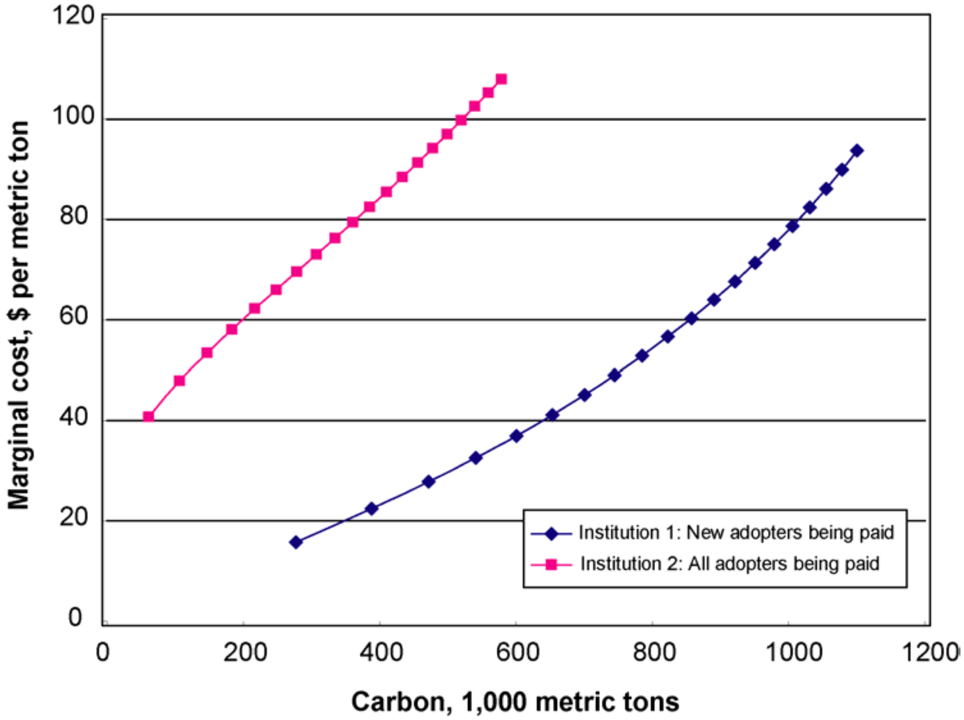

FIGURE 2. Marginal cost of carbon sequestration under alternative policy regimes and full information on field-level carbon sequestration potential

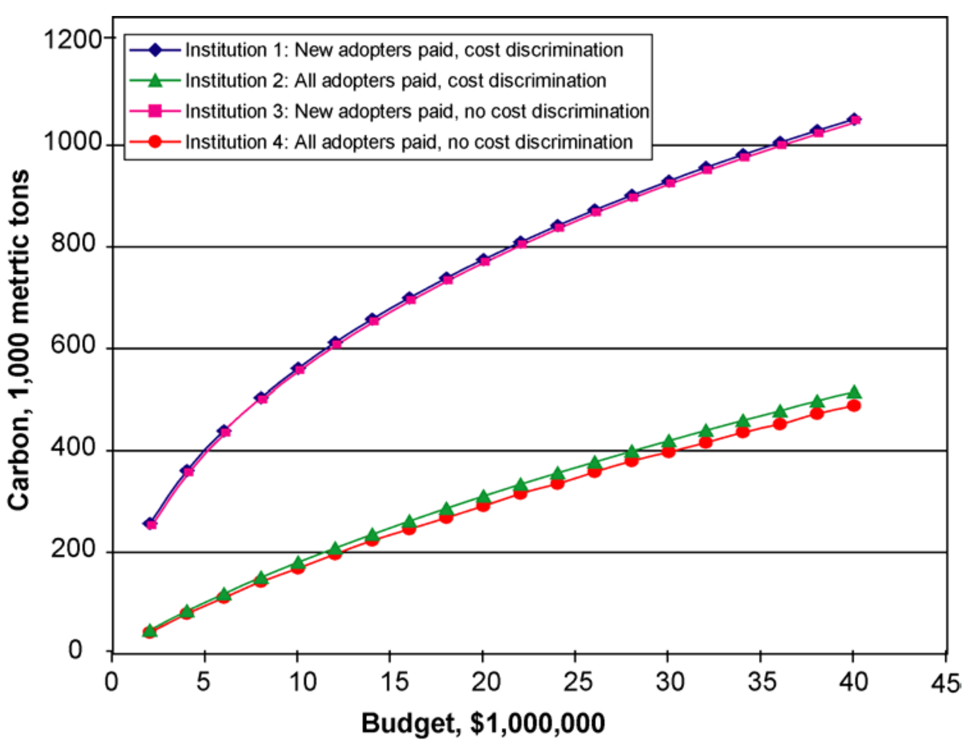

FIGURE 3. Carbon sequestration with county-level information

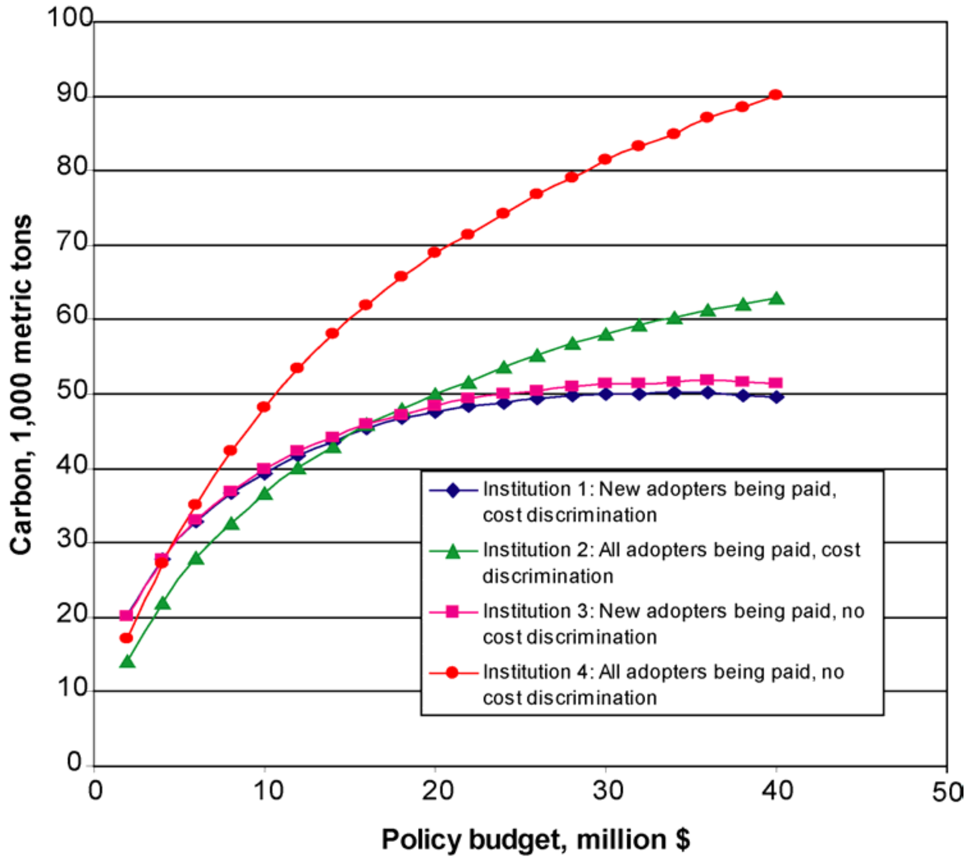

FIGURE 4. Carbon gain due to field-level information as opposed to county-level information

targeting. As expected at all budget levels, $Q(\mathbf{s}_1^I)-Q(\mathbf{s}_1^{99})<Q(\mathbf{s}_3^I)-Q(\mathbf{s}_3^{99})$ (diamonds versus squares, payment to new adopters only) and $Q(\mathbf{s}_2^I)-Q(\mathbf{s}_2^{99})<Q(\mathbf{s}_4^I)-Q(\mathbf{s}_4^{99})$ (triangles versus circles, payment to all adopters). Interestingly, the ranking of the policies when all are paid versus when only new adopters are paid depends on the budget level. At low levels of the budget, the carbon gain is higher for the policies that pay new adopters only, that is, $Q(\mathbf{s}_4^I)-Q(\mathbf{s}_4^{99})<Q(\mathbf{s}_3^I)-Q(\mathbf{s}_3^{99})$ (without cost discrimination) and $Q(\mathbf{s}_2^I)-Q(\mathbf{s}_2^{99})<Q(\mathbf{s}_1^I)-Q(\mathbf{s}_1^{99})$ (with cost discrimination), while at the higher levels the ranking is reversed. As Figure 4 shows, the reversal occurs at around $5 million for no cost discrimination policies (circles versus squares), and at around $16 million for cost discriminating policies (triangles versus diamonds).

These results suggest that the value of improved measurement technology depends not only on which policy institution is chosen to implement increased carbon sequestration but also on the overall sequestration level. If agriculture plays a significant role in addressing the atmospheric accumulation of carbon, the budget level will need to be set relatively high, in which case the greatest benefits to improved measurement technology will occur if a policy that pays all adopters is chosen. If soil carbon sequestration is to play only a small part in the overall basket of carbon reduction strategies, the optimally chosen carbon sequestration budget will be low and the value of improved measurement technology will be highest under a policy that pays only new adopters.

Finally, we computed the monetary valuation of the gain in carbon due to better measurement technologies using equation (14). Note that this valuation assumes that the sequestration program is designed efficiently and thus the social marginal value of carbon reductions equals $1/\lambda_1^I$. The estimated cost savings for institutions 1 and 4 are provided in Figure 5 and suggest a high monetary value associated with investing in field-scale measurement technology. These cost savings range anywhere from 11.2 percent of the total budget to over 47.3 percent.[10]

Conclusions

Accurate technology for field-scale carbon assessment is a necessary ingredient for the implementation of policies that target subsidy payments to farms that provide the greatest carbon benefits per dollar spent. The development of such technology will allow the implementation of more efficient policies than can be implemented in their absence. This observation forms the basis for estimating the benefits of developing field-scale measurement technology for carbon sequestration. Since the availability of such technology would allow the adoption of more efficient policies, the cost savings associated with these policies can be viewed as the value of the improved technology. If the cost savings are high, it would be socially worthwhile to invest significantly in the development of such technologies. If the cost savings are low, significant investment would not be warranted.

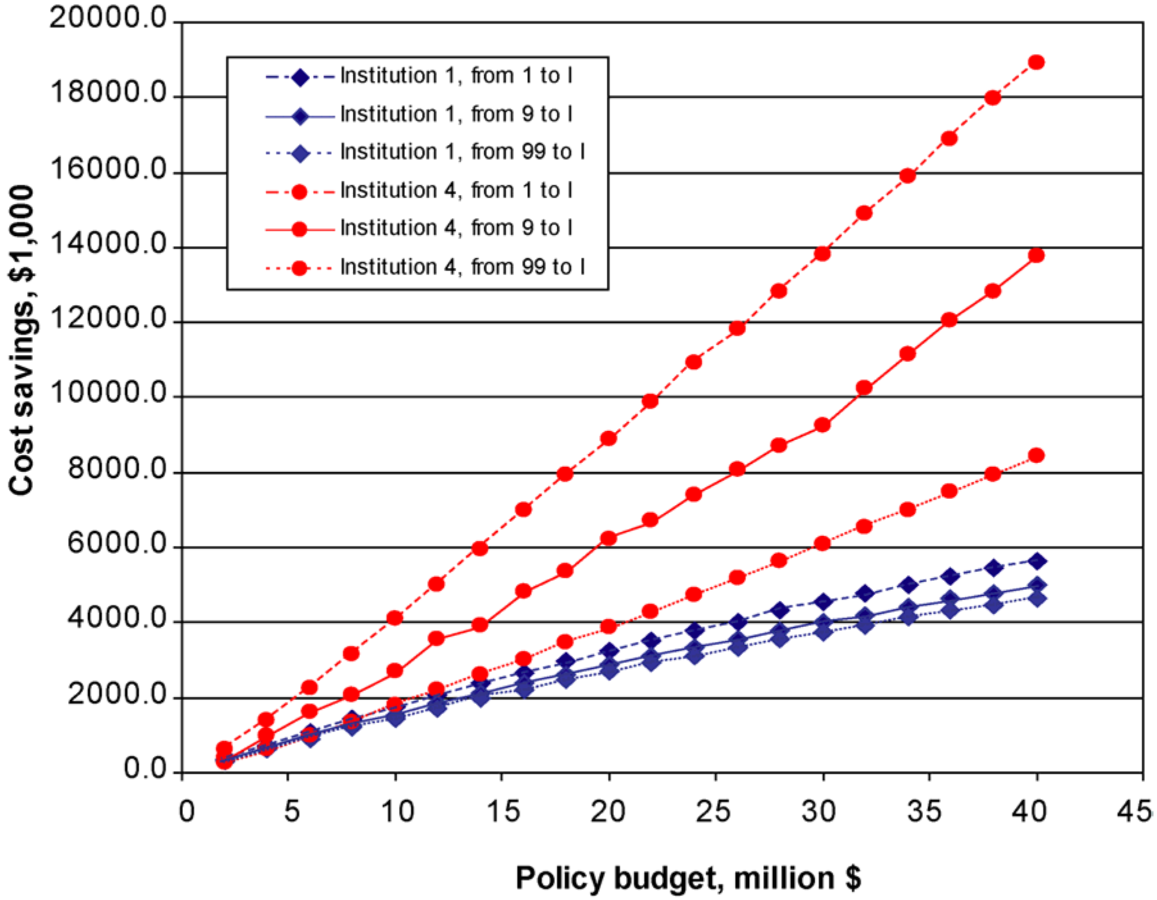

FIGURE 5. Cost savings due to availability of field-level carbon sequestration information under alternative subsidy institutions

In this study, we estimated relatively large cost savings for improved targeting of conservation tillage subsidy policies in Iowa. In the absence of field-scale measurement technologies, up to 64 percent less carbon can be sequestered than if field-scale measurement technology is available. In monetary terms, this translates into cost savings of over $612,000.

Also of note is the important role that the payment of subsidies to existing providers of carbon sequestration can have, both in the value of the technological improvements and in the overall amount of carbon sequestration that can be purchased with a given budget. More than any other policy dimension we investigated, this design feature of a subsidy program will significantly affect its efficacy in terms of carbon storage.

The results are influenced by the variability among producers in terms of the costs of conservation tillage adoption and/or in terms of the carbon sequestration potential. Consequently, the results may not transfer immediately to other regions. However, there is little reason to think that Iowa is more heterogeneous than other regions in terms of its suitability for carbon sequestration; thus, there may be many locations that will exhibit even higher returns from improved measurement technology than those found here.

The models and results presented here suggest a number of important areas for future research. A variety of other policy approaches for encouraging soil carbon sequestration are possible, including carbon markets, taxes, and hybrids, and these approaches in turn affect the value of carbon measurement technology. Assessing the value of these technologies under the alternatives of interest to policymakers would be a valuable addition to the current results. Likewise, it would be valuable to study the optimal mechanism given a particular level of technological measurement accuracy. As the technology improves and the spatial accuracy of measurement improves, it may be optimal to change the structure of the policy mechanism.

Endnotes

1. See, for example, project summaries from the multi-institutional research project, Consortium for the Agricultural Soils Mitigation of Greenhouse Gases, available online at *www.casmgs.colostate.edu*.

2. For simplicity, we do not consider private information on the cost of adoption. Presumably, the government can use a bidding mechanism like that in the Conservation Reserve Program (CRP) enrollment through which farmers fully reveal their private information on adoption costs.

3. We implicitly assume that the costs of applying the measurement technology are not part of the budget constraint. In measuring soil carbon, a promising technology is GIS based where the variable cost of applying the technology is low.

4. The regulator is thus paying for both previous acreage that sequestered carbon and any initial levels of carbon sequestered in fields that newly adopted sequestering practices provide.

5. This is conceptually similar to emission based permit systems when pollution damage varies spatially and trades are allowed on a one-to-one basis within pre-defined zones. See Baumol and Oates 1988.

6. For example, carbon sinks in agricultural soils met with some substantial skepticism internationally during the Kyoto discussion as some expressed concern that carbon already stored below ground might be claimed to satisfy the targets.

7. Definitions of the data as well as parameter estimates are provided in Kurkalova, Kling, and Zhao 2003.

8. Earlier versions of EPIC were called the Erosion Productivity Impact Calculator (Williams 1990).

9. The CSP of the 2002 farm bill provides $2 billion for five years (U.S. Congress 2002). Even if Iowa crop producers get one-tenth of the yearly total, the program funding is limited to $40 million per year.

10. It is important to keep in mind that the values reported in Figure 5 refer to the cost savings that could be accrued in the state of Iowa alone. Assuming that the development of such technology that is appropriate for Iowa would also be appropriate for other states and regions, the full benefits are likely to be much larger.

Appendix A

The Positive Value of Improved Measurement Technology

To show that $Q(\bullet)$ increases when partition $\{\mathcal{I}_k, k=1,\ldots,K\}$ becomes finer, consider, without loss of generality, institution 1. Note that the optimization problem in equation (1) can be transformed to

$$\begin{aligned} &\max_{\mathbf{s}} \ \mathrm{A}\sum_{i=1}^{I} p_i(s_i)\theta_i \\ \text{s.t.} \quad &\sum_{i=1}^{I}\big(p_i(s_i)-p_i(0)\big)A_i s_i = \mathrm{B}; \quad \mathrm{s}_i \geq 0, \end{aligned} \tag{A.1}$$

where $A=\sum_{i=1}^{I} A_i$ is the total acreage, and $\theta_i = A_i q_i / A$ is farm *i*'s "share" of the total carbon potential of all farms. Since $\sum_{i=1}^{I}\theta_i = 1$ and $\theta_i \geq 0$, we also can regard $\theta_i, i=1,\ldots,I$ as probabilities, and (A.1) as maximization of a certain expected value.

Now consider partition $\{\mathcal{I}_k, k=1,\ldots,K\}$. Corresponding to equation (6), we can define

$$\theta_{i_k}^k = \frac{A_{i_k}}{\sum_{j\in\mathcal{I}_k} A_j}\sum_{j\in\mathcal{I}_k}\theta_j \ , \tag{A.2}$$

where $\theta_j = A_j q^k / A$, $j \in \mathcal{I}_k$. Equation (A.2) measures the share of farm i_k belonging to subset *k*, in the total carbon potential. Notice that $\theta_{i_k}^k$ utilizes carbon information of subset *k* only, and $\sum_{k=1}^{K}\sum_{i_k\in\mathcal{I}_k}\theta_{i_k}^k = 1$. Then equation (7) can be rewritten as

$$\max_{\mathbf{s}} \; \mathrm{A}\sum_{k=1}^{K}\sum_{i_k \in \mathcal{I}_k} p_{i_k}(s_{i_k})\theta_{i_k}^{k}$$
$$\text{s.t.} \qquad \sum_{k=1}^{K}\left[\sum_{i_k \in \mathcal{I}_k}\left(p_{i_k}(s_{i_k}) - p_{i_k}(0)\right)A_{i_k} s_{i_k}\right] = \mathrm{B}; \quad s_i \geq 0,\; i \in \mathcal{I} \tag{A.3}$$

Equation (A.2) shows that $(\theta_i, i = 1,...,I)$ is sufficient for $(\theta_{i_k}^{k}, i_k \in \mathcal{I}_k, k = 1,...,K)$: the latter in a subset is a weighted average of the former in that subset. Then Blackwell's Theorem implies that the former is more informative, or the payoff in (A.1) is higher than in (A.3) (Kihlstrom 1984).

Similarly, we can compare two partitions: partition $\{\mathcal{I}_k, k = 1,...,K\}$ is finer than $\{\mathcal{I}_k, k = 1,...,K'\}$ if the former is a subset of the latter. Then, repeating the previous procedure, we can show that the expected carbon under the former is higher. This result also holds true under other institutions.

Appendix B

Details on Computations

Given budget level B, the numerical solution to problem (1) (or (4), (7), or (9), depending on the informational and institutional settings) was found using the Secant algorithm (see, for example, Burden and Faires1985). Specifically, we started with the first approximation, $\lambda^{(1)}$, and solved the equations in (3) (or (5), (8), or (11), respectively) with the right-hand side equal to $\lambda^{(1)}$ for $s_i^{(1)}$ at each data point i for which the solution exists. The cost of the policy at the solution $\mathbf{s}^{(1)}$ was compared to the budget level B. If the relative difference between the cost and the budget was less than a chosen tolerance level, then the value of $\lambda^{(1)}$ was accepted as the solution. Otherwise, we repeated the procedure of finding the solution $\mathbf{s}^{(2)}$ of the set of equations (3) (or (5), (8), or (11), respectively) for the second approximation, $\lambda^{(2)}$. Again, if the relative error in matching the budget was less than the tolerance level, the value of $\lambda^{(2)}$ was accepted as the solution. Otherwise, the λ was updated using the Secant method and the procedure of updating λ and finding the corresponding solution $\mathbf{s}$ was repeated until the relative difference between two consecutive approximations to λ was within a chosen tolerance level.

References

Antle, J.M., S.M. Capalbo, and S. Mooney. 2002. "Farming the Environment: Spatial Variation and Economic Efficiency in Soil; Developing Policies for Carbon Sequestration and Agriculture." *Choices*, Fall, pp. 24-25.

Antle, J.M., S.M. Capalbo, S. Mooney, E.T. Elliott, and K.H. Paustian. 2003. "Spatial Heterogeneity, Contract Design, and the Efficiency of Carbon Sequestration Policies for Agriculture." *Journal of Environmental Economics and Management*, in press. <http://www.elsevier.com/jeem> (accessed May 2003).

Baumol, W.J., and W.E. Oates. 1988. *The Theory of Environmental Policy*, 2nd ed. Cambridge: Cambridge University Press.

Burden, R.L., and J.D. Faires. 1985. *Numerical Analysis*. Boston: PWS Publishers.

Feng, H., J. Zhao, and C.L. Kling. 2003. "Towards Implementing Carbon Markets in Agriculture." *Choices,* Spring, pp. 16-19.

Izaurralde, R.C., J.R. Williams, W.B. McGill, N.J. Rosenberg, and M.C. Quiroga Jakas. 2002. "Simulating Soil C Dynamics with EPIC: Model Description and Testing Against Long-Term Data." *Agronomy Abstracts*, CD-ROM. American Society of Agronomy, Madison, WI.

Kihlstrom, R.E. 1984. "A 'Bayesian' Exposition of Blackwell's Theorem on the Comparison of Experiments." Chap. 2 in *Bayesian Models in Economic Theory*. Edited by M. Boyer and R.E. Kihlstrom. New York: Elsevier Science Publishers.

Kurkalova, L.A., C.L. Kling, and J. Zhao. 2003. "Green Subsidies in Agriculture: Estimating the Adoption Costs of Conservation Tillage from Observed Behavior." CARD Working Paper 01-WP 286. Center for Agricultural and Rural Development, Iowa State University. March. <http://www.card.iastate.edu/publications/DBS/PDFFiles/01wp286.pdf> (accessed April 2003).

Lal, R., J.M. Kimble, R.F. Follet, and C.V. Cole. 1998. *The Potential of U.S. Cropland to Sequester Carbon and Mitigate the Greenhouse Effect*. Ann Arbor, MI: Sleeping Bear Press.

Millock, K., D. Sunding, and D. Zilberman. 2002. "Regulating Pollution with Endogenous Monitoring." *Journal of Environmental Economics and Management* 44: 221-41.

Mooney, S., J.M. Antle, S.M. Capalbo, and K.H. Paustian. 2002. "Contracting for Soil Carbon Credits: Design and Costs of Measurement and Monitoring," Staff Paper 2002-01, Department of Agricultural Economics and Economics, Montana State University-Bozeman. May.

———. 2003. "Influence of Project Scale on the Costs of Measuring Soil C Sequestration." *Environmental Management* in press.

Nusser, S.M., and J.J. Goebel. 1997. "The National Resources Inventory: A Long-Term Multi-Resource Monitoring Programme." *Environmental and Ecological Statistics* 4: 181-204.

Parks, P.J., and I.W. Hardie. 1995. “Least-Cost Forest Carbon Reserves: Cost-Effective Subsidies to Convert Marginal Agricultural Land to Forests.” *Land Economics* 71(February): 122-36.

Parton, W.J., D.S. Ojima, C.V. Cole, and D.S. Schimel. 1994. “A General Model for Soil Organic Matter Dynamics: Sensitivity to Litter Chemistry, Texture and Management.” SSSA Spec. Pub. vol. 39, pp. 147-67. Soil Science Society of America. Madison, WI.

Pautsch, G.R., L.A. Kurkalova, B.A. Babcock, and C.L. Kling. 2001. “The Efficiency of Sequestering Carbon in Agricultural Soils.” *Contemporary Economic Policy* 19(April): 123-34.

U.S. Congress. 2002. *Farm Security and Rural Investment Act.* 107th Congress, 2nd Session. H.R. 2646 (P.L. 107-171). Signed into law May 13. <http://frwebgate.access.gpo.gov/cgi-bin/getdoc.cgi?dbname=107_cong_bills&docid=f:h2646enr.txt.pdf> (accessed December 2002).

U.S. Department of Agriculture, Soil Conservation Service (USDA-SCS). 1994. *The 1992 National Resources Inventory Database*. Washington, DC.

Williams, J.R. 1990. “The Erosion Productivity Impact Calculator (EPIC) Model: A Case History.” *Philosophical Transactions: Biological Sciences* 329(1225): 421-28.